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Driving EU sustainability: Promoting the circular economy through municipal waste efficiency

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ABSTRACT

The need to balance ecosystems and ensure the well-being of all people underlines the urgency of closing product life cycles. In recent years, the circular economy (CE) has emerged as one of the most relevant factors in achieving the Sustainable Development Goals. This paper presents a systematic literature review (SLR) of waste management efficiency at the European level. Furthermore, it presents a standard data envelopment analysis (DEA) of 27 European countries over the period 2017–2021, focused on municipal waste. Three models (i.e., economic, technical, sustainable) are proposed to optimise the rates of municipal waste recycling and circular material use.

The SLR, based on an initial set of 216 articles that was subsequently refined through double screening to 31, highlights the strategic role of the waste management, recycling and municipal solid waste triangle. The results of the DEA indicate stronger synergy between technical and sustainability dimensions than between economic and sustainability components. Moreover, they highlight fragmented performance in Europe, with distinct clusters of countries emerging as top performers in each of the three models, and the Netherlands, Slovenia, France, Italy, Germany and Sweden demonstrating superior performance for both CE outcomes and sustainable performance. Overall, the results emphasise the strategic role played by technology in facilitating an efficient circular model of municipal waste management to minimise landfilling and other environmentally detrimental practices, thereby stimulating the development of sustainable communities for optimised waste management, in line with broader sustainability objectives.

1. Introduction

The circular economy (CE) is widely debated in the literature, and there is no consensus on the concrete paths that may lead to its emergence. Over time, it has become closely associated with reuse and recycling, representing fundamental principles of ecology (Kirchherr, 2023). However, various limitations to CE development have been recognised, including consumer cultural barriers and hesitant corporate cultures (Kirchherr et al., 2018), failure to consider the social implications (Mies and Gold, 2021), challenges related to the quality and availability of secondary materials (Hsu et al., 2022) and incomplete data on the benefits of circular systems to the natural environment (Harris et al., 2021).

A key component of Sustainable Development Goal (SDG) 12 is the monitoring of CE systems, including an assessment of their advantages and disadvantages (Sharma et al., 2023; Voukkali et al., 2023). Research has shown a positive relationship between CE innovation and CE performance, underscoring the importance of creating environments that are able to foster new approaches and support and fund their implementation (Vranjanac et al., 2023). The achievement of circularity requires a holistic system perspective encompassing production, consumption and waste management (Bianchi and Cordella, 2023). Central to this effort are stringent policies aimed at countering the illegal flow of waste, which can undermine CE practices (D'Amato et al., 2018). Moreover, previous analyses have demonstrated the significant ecological benefits of reusing water, energy and materials, reinforcing the value of circular strategies for sustainability (Nikolaou and Tsagarakis, 2021; Tarpani and Azapagic, 2023).

Within this context, Europe's journey towards climate neutrality

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Nomenclature

Abbreviations

BoD	Benefit of Doubt
CE	Circular Economy
CRS	Constant Returns to Scale
DEA	Data Envelopment Analysis
DMU	Decision-Making Unit
EU	European Union
MSW	Municipal Solid Waste
MSWM	Municipal Solid Waste Management
RTS	Returns To Scale
SDG	Sustainable Development Goal
SLR	Systematic Literature Review
VRS	Variable Returns to Scale

Symbols

f	Weight of the peers in the DEA
n	Number of DMUs considered in the DEA
p	Number of inputs in the DEA
q	Number of outputs in the DEA
$x \in R_{+}^{p}$	A vector of inputs
(x,y)	A country (DMU) with inputs x and outputs y
$y \in R_{+}^{q}$	A vector of outputs
$\widehat{\varphi}$	DEA efficiency score output-oriented
Ψ	Production set
$\widehat{\Psi}_{DEA}$	Production set estimated through DEA

warrants particular attention. A key metric that is used to monitor progress towards this end is the definition of waste as a product (i.e., secondary raw material), in accordance with the European Commission's Waste Framework Directive. While recycling remains the most widely used circular strategy (De Pascale et al., 2023), there is a need for EU Member States to increase the amount of secondary raw material they feed back into the production cycle (Chioatto and Sospiro, 2023). Sustainable waste management has been linked to improved quality of life (Romano et al., 2022), but it often relies on government support for research and development in waste reduction technologies, as well as educational campaigns (Hondroyiannis et al., 2024a).

Recent scholarship has predominantly focused on the waste type known as municipal solid waste (MSW). Studies have shown that specific technologies may be used to maximise the recovery of resources from MSW (Ambaye et al., 2023). However, strategic analyses have emphasised the necessity of a pragmatic, stakeholder-inclusive approach to MSW management, employing quantitative methods to identify optimal waste management strategies within a sustainable framework (D'Adamo et al., 2023).

Composite indices have been employed to compare MSW management systems across European countries (Castillo-Giménez et al., 2019a) and waste categories (Colasante et al., 2022), and data envelopment analysis (DEA) has been applied to evaluate efficiency and performance across countries (Chioatto et al., 2024). Research has shown that central and northern regions of Europe perform better than eastern and southern regions, with lower circularity rates observed in the south, relative to the north (Hondroyiannis et al., 2024b). Similarly, a study using a Eurostat index comprised of various CE indicators demonstrated better performance in western, compared to eastern, European countries (D'Adamo et al., 2024b).

This paper aims at exploring the relationship between MSW management and CE models across European countries. The contribution to the literature is twofold: (1) it provides a systematic literature review (SLR) of previous research on waste management efficiency at the European national level; and (2) it employs DEA to develop and assess three quantitative models addressing the technical, economic and sustainable dimensions of MSW management, and compares the results with scores of the recently established CE indicator (D'Adamo et al., 2024b). Through this dual approach, the work provides new empirical evidence on the efficiency of MSW management in Europe (in the years 2017–2021) and contributes to the formulation of evidence-based policy suggestions aimed at advancing sustainability, considering its multiple facets and interrelationship with CE principles.

2. Literature review

Despite the existence of several meta-analyses on municipal waste management (see, e.g., Campitelli and Schebek, 2020; Maalouf and Agamuthu, 2023; Yang et al., 2023), to the best of our knowledge, no prior review has pursued an efficiency analysis at the macro (i.e., country) level within the European context. To address this research gap, we conducted an SLR adhering to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA; Page et al. (2021) framework and following the procedure described by Avenali et al. (2023).

The review focused on the application of both non-parametric and parametric methods to the MSW cycle within a CE framework, across European countries. As eligibility criteria, we selected reviews and articles written in English, published between 2015 and 2024 and indexed in Scopus. Moreover, we required the articles to analyse MSW management at a macro level (i.e., considering countries as the unit of analysis). An initial set of 216 articles was identified, which, following a rigorous double screening, was refined to 31 key publications. Additional technical details regarding the SLR are provided in the supplementary materials (Figs. S1–S5, Tables S1–S2 (Linnenluecke et al., 2019)). The thematic map highlights the strategic importance of issues related to the waste management, recycling and MSW triangle, in terms of their level of development and relevance (Lavigne et al., 2019).

The SLR revealed that 16 of the analysed articles employed parametric methods to assess waste management efficiency. The most frequently used method was panel regression analysis, as evidenced in several studies (Apostu et al., 2023; Busu, 2019; Busu and Trica, 2019; Pao and Chen, 2021; Pelau and Chinie, 2018). Notably, Azwardi et al. (2023) employed a variation on the standard panel data method, using common effects, fixed effects and random effects models while proposing a test for selecting the most appropriate method. In contrast, Chen and Pao (2022) opted for the vector error correction model to analyse non-stationary time series data. Other parametric approaches included analytical hierarchy processes (Colasante et al., 2022; D'Inverno et al., 2024), environmental Kuznets curve analysis (Arbulú et al., 2015; Ari and Şentürk, 2020), linear regression and its variations (Banacu et al., 2019; Hondroyiannis et al., 2024b; Smejkalováa et al., 2020), clustering techniques (López-Portillo et al., 2021) and compliance index models (Egüez, 2021). However, many of these methods are subject to statistical limitations, primarily related to assumptions regarding the functional form of the production (or cost) functions and the distribution of residuals. Given these constraints, our analysis also attended to studies applying non-parametric methods, which tend to offer greater flexibility. Among the 15 studies identified that applied such methods, the most frequently employed approach was DEA. DEA represents a robust technique for evaluating the efficiency of a decision-making unit (DMU) against a set of similar DMUs. Unlike parametric estimation methods such as linear regression, DEA does not impose a priori assumptions about the functional form of the production frontier relating inputs to outputs, making it applicable to a variety of contexts. Most of the studies identified in the SLR adopted the standard (i.e., classical or basic) DEA model (Chioatto et al., 2023; Giannakitsidou et al., 2020; Halkos and Papageorgiou, 2016; Halkos and Petrou, 2019a, 2019b, 2019c; Marques and Teixeira, 2022; Ríos and Picazo-Tadeo, 2021), with either an input orientation (i.e., fixing outputs and technology while minimising inputs) or output orientation (i.e., fixing inputs and technology while maximising outputs). These models assumed either constant returns to scale (CRS) or variable returns to scale (VRS), depending on the specific objectives of their analyses. Ye et al. (2022) enhanced the robustness of their DEA results by applying the bootstrap method proposed by Simar and Wilson (1998).

Additionally, several of the investigated studies (Castillo-Giménez et al., 2019a, 2019b; Chioatto et al., 2024; Milanović et al., 2022; Rogge et al., 2017) employed a DEA benefit-of-doubt (BoD) model to construct composite indicators for inputs or outputs using the linear programming weights of the DEA model. Halkos and Aslanidis (2023) leveraged non-parametric techniques to assess the evolution of efficiency over time, using the Malmquist Productivity Index (MPI; Caves et al. (1982)) to compare performance across three distinct periods: 1998–1999, 2008–2009 and 2018–2019. Some authors also advocated for the robust, conditional version of the BoD model's directional distance function, which not only ranks spatial entities but also identifies their relative strengths and weaknesses (Lavigne et al., 2019).

Our SLR identified four primary themes within studies employing efficiency analysis techniques:

- waste treatment efficiency (Castillo-Giménez et al., 2019a, 2019b; Halkos and Petrou, 2019a; Ríos and Picazo-Tadeo, 2021);
- environmental effects of efficient waste management (Giannakitsidou et al., 2020; Halkos and Papageorgiou, 2016; Halkos and Petrou, 2019b; Ye et al., 2022);
- relationship between waste management and the CE (Halkos and Aslanidis, 2023; Marques and Teixeira, 2022; Milanović et al., 2022); and
- social aspects of waste management (Chioatto et al., 2023; Halkos and Petrou, 2019c).

Some authors focused on the economic, social and environmental aspects of sustainable waste management, using DEA BoD to construct composite indicators (Chioatto et al., 2024; Rogge et al., 2017). Not all studies, however, assessed the efficiency of MSW management at the macro level; several focused on specific European countries while analysing performance at the NUTS-2 regional level (Chioatto et al., 2023, 2024; Halkos and Papageorgiou, 2016; Rogge et al., 2017). The majority of the reviewed articles applied some form of DEA, including slacks-based DEA analysis combined with multi-criteria decision making and clustering techniques (Castillo-Giménez et al., 2019a, 2019b), the bootstrap method and DEA estimation of bias-corrected efficiency scores (Halkos and Petrou, 2019a, 2019b, 2019c), DEA with a fractional regression to identify key drivers of efficiency (Marques and Teixeira, 2022), DEA incorporating value judgment (Giannakitsidou et al., 2020) and a three-stage DEA model (Ye et al., 2022). The observed methodological diversity reflects the inherent complexity of assessing environmental performance and underscores the necessity of considering multiple perspectives based on the specific research questions. Each approach presents distinct advantages and limitations, and the choice of method can significantly influence the results obtained. Thus, the interpretation of environmental performance assessments must always consider the methodological context in which they were produced.

The SLR revealed considerable variability in waste management performance within Europe. Denmark, Austria and Germany tended to consistently rank among the highest performers in various studies (Castillo-Giménez et al., 2019a; Giannakitsidou et al., 2020), while Bulgaria, Croatia and Romania frequently occupied the lower ranks. Some degree of consistency across studies was noticeable. For example, Slovenia was consistently found to exhibit high performance across several indicators, often ranking first (Halkos and Petrou, 2019a, 2019b, 2019c). However, some significant discrepancies could also be observed. For example, Finland demonstrated mixed performance, ranking relatively low on Castillo-Giménez et al.'s (2019a) composite indicator but achieving high efficiency scores on the indicator employed by Halkos and Petrou (2019a). Other countries, such as Hungary, displayed exceptional performance on specific indicators – scoring highest on two environmental indicators in Halkos and Petrou (2019b) – and lower rankings on others. Sweden, though not always positioned at the very top of the rankings, consistently performed well across most indicators (Marques and Teixeira, 2022; Milanović et al., 2022). These divergences reflect the complex and multidimensional nature of MSW management, as well as (potentially) variations in the methodologies employed or the studies' respective research focuses (with respect to the different domains of sustainability).

In summary, the large majority of the analysed studies employed DEA to examine MSW management efficiency at the macro level within Europe (Simões and Marques, 2012). The multi-input, multi-output framework of DEA renders it particularly well-suited to addressing the circularity and sustainability dimensions of waste management. The investigated articles supported our choice of economic, technical and sustainability variables for the DEA assessment of MSW management. Moreover, the results of the DEA aligned with those obtained through MCDA using the CE indicator proposed by D'Adamo et al. (2024a), as detailed in Table S3.

3. Methods

This section presents the data (Section 3.1), the methodology employed (Section 3.2) and the specification of the models developed (Section 3.3) in the present study.

3.1. Data

All study data were sourced from EUROSTAT (Table S4), with reference to 27 EU Member States during the period 2017–2021. The following variables were collected:

- municipal waste generated, in kilogrammes per capita (henceforth ‘MSW generation’);
- municipal waste disposed of by energy recovery, in kilogrammes per capita;
- municipal waste disposed of by landfill, in kilogrammes per capita;
- municipal waste disposed of by incineration, in kilogrammes per capita;
- municipal waste recycling rate, in percentage of total waste generated (henceforth ‘recycle rate’);
- circular material use rate, in percentage of total material use;
- greenhouse gas emissions from production activities, in kilogrammes per capita (henceforth ‘GHG Emissions’). These statistics include “all emissions that occur throughout the production chain of a product that arrives in the EU for final consumption or investment – irrespective of the industry or country where the emission occurred” (European Commission, 2024);
- private investment related to CE sectors, in percentage of gross domestic product (GDP); and
- persons employed in CE sectors, in percentage of total employment.

Figs. S6–S14 illustrate the distribution of these variables. To ensure accuracy and consistency, we incorporated data on waste disposal methods prioritised by the EU Waste Framework Directive (i.e., energy recovery, landfilling, incineration) (The European Parliament and the Council of the European Union, 2008), to avoid complications arising from zero values in the dataset. In this article, we refer to this new aggregate variable as ‘bottom of the waste hierarchy disposal’. Table 1 presents the descriptive statistics for each variable. Descriptive statistics for each year are presented in Table S5 in the supplementary materials.

Table 1
Summary descriptive statistics for the analysed variables. SD stands for standard deviation. Source: authors' elaboration based on EUROSTAT data (2024).

	Min	Mean	Median	Max	SD
MSW generation	272	520.85	499	844	131.89
Bottom of the waste hierarchy disposal	97	292.56	270	636	95.76
Recycle rate	9.10	39.28	40.20	70.30	14.71
Circular material use rate	1.40	9.13	7.60	28.50	6.44
GHG Emissions	3620.34	7562.91	7039.77	16,135.66	2862.51
Private investment related to CE	0.10	0.72	0.70	1.60	0.32
Persons employed in CE	0.40	1.83	1.80	3.50	0.40

For Ireland, some data for 2021 were not available. Thus, we utilised 2020 data for the year 2021, assuming relatively constant values between these years.

3.2. Data envelopment analysis

As described in Section 2, DEA is the most widely used non-parametric efficiency method for evaluating waste management efficiency at a country level. The technique uses linear programming to estimate an efficient frontier against which a DMU's performance can be compared to its peers, thereby deriving an efficiency value for each unit. Thus, efficiency is based on the output-to-input ratio of a unit relative to a benchmark or efficient frontier (Daraio and Simar, 2007). Efficiency analysis can be traced back to the seminal work of Farrell (1957), which operationalised efficiency analysis for multiple inputs and outputs.

The DEA model operates under certain assumptions: (1) free disposability (i.e., the ability to destroy goods without cost), (2) convexity and (3) no free lunches (i.e., no output allowed for zero input values of production) on the production set Ψ. The original DEA model was further developed by Charnes et al. (1978), who applied linear programming to observational data. In this formulation, the efficient frontier assumes constant returns to scale (CRS). Banker et al. (1984) subsequently extended the DEA model to include variable returns to scale (VRS).

In the present study, to estimate the efficiency of a DMU (e.g., a country), we considered a production set Ψ defined by a set of vectors of p inputs $x \in R_+^p$, and a set of vectors of q outputs $y \in R_+^q$, defining the production set as:

$$\Psi = \left\{ (x, y) \in R_+^{p+q} \,|x \text{ can produce } y \right\} \tag{1}$$

with *(x,y)* representing a DMU using x inputs to produce y outputs, and Ψ representing the true but unknown production set, estimated through DEA and denoted by $\widehat{\Psi}_{DEA}$. In DEA analysis, efficiency is estimated by the radial distance of each DMU to the efficient frontier. The input-oriented DEA model aims at proportionally reducing all inputs while maintaining a constant level of outputs to reach the efficient frontier. In contrast, the output-oriented DEA model aims at proportionally increasing all outputs while keeping a constant level of inputs to reach the efficient frontier. In the present study, we applied an output-oriented DEA. The DEA efficiency score $\widehat{\varphi}$ for a country represented by the vector (x, y), was defined as:

$$\widehat{\varphi}(x, y)_{DEA} = \{sup\varphi > 0 | (x, \varphi y) \in \widehat{\Psi}_{DEA}.\} \tag{2}$$

The efficiency score $\widehat{\varphi}$ for each country was calculated by solving the following linear programming problem on n DMUs:

$$max(\varphi) \tag{3}$$

s.t.

$$\sum_{j=1}^{n} f_j x_{ij} - x_{i0} \leq 0 \forall i, i = 1, \dots, p$$

$$\varphi y_{r00} - \sum_{j=1}^{n} f_j y_j \leq 0, \forall r, r = 1, \dots, q$$

$$f_j \geq 0$$

$$\sum_{j=1}^{n} f_j = 1 \tag{4}$$

with f denoting the weight of peers. This was a VRS model. However, dropping eq. (4) gave us a CRS model.

In our modelling to determine whether we had CRS or VRS frontiers and whether production sets were convex, we applied the tests proposed by Kneip et al. (2015) to determine returns to scale and the convexity hypothesis, using the FEAR R package (Wilson, 2008). This approach ensured that decisions were based on statistical significance (considering the p-values returned by the tests). When a p-value fell below the threshold (i.e., 0.05), this indicated that the observed results were unlikely to have occurred by chance, leading us to reject the null hypothesis in favour of the alternative hypothesis. For the convexity test, the null hypothesis was the convexity assumption of the production set, while the alternative hypothesis was the non-convexity assumption. For the returns to scale test, the null hypothesis was the CRS assumption of the production set, while the alternative hypothesis was the VRS assumption. The DEA analyses were conducted in R programming language (RC Team, 2013), using the FEAR package cited above and the Benchmarking package (Bogetoft and Otto, 2011). DEA is commonly applied in various sustainability contexts (Daraio et al., 2023; Lombardi et al., 2021; Shi et al., 2023).

3.3. Technical, economic and sustainability models

We explored three efficiency models to address the gap identified in our SLR regarding CE aspects, and particularly the integration of variables related to circularity. Furthermore, our research aimed at leveraging these models to establish links between economic, technical and sustainability variables within the context of municipal solid waste management (MSWM). Given the limited number of observations available, we assumed that no significant technological advancements occurred during the period under analysis. Consequently, we aggregated all years in estimation of the efficient frontier.

Our novel approach addressed the need to align decision making processes in MSWM with circular approaches. We anticipated that, by employing DEA models to integrate economic, technical and sustainability variables, we would produce valuable insights to inform and guide decision makers in their pursuit of circularity within MSWM.

In detail, the work identified three distinct models: Model 1 (technical), Model 2 (economic) and Model 3 (sustainability).

Based on the p-values obtained from the returns to scale and convexity tests presented in Section 3.2 and reported in Table 2, we selected a DEA VRS specification for Model 1 and a DEA CRS specification for Models 2 and 3.

- Model 1 – technical model (Fig. 1) with VRS

Inputs: MSW generation, bottom of the waste hierarchy disposal, GHG emissions.
Outputs: Recycle rate, circular material use rate.

Table 2
Convexity and returns to scale (RTS) tests: p-values.

Model	Convexity test p-value	RTS test p-value	DEA model chosen
Model 1	0.541	<0.001	DEA VRS
Model 2	0.998	0.439	DEA CRS
Model 3	0.739	0.113	DEA CRS

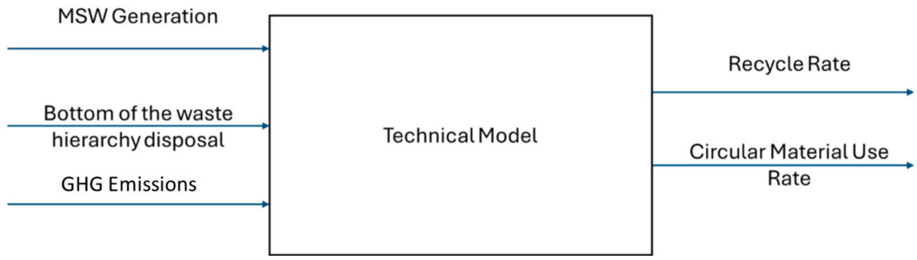

Fig. 1. Technical model. Incoming arrows in the central block indicate model inputs, while outgoing arrows indicate model outputs.

This model focused on the technical aspects of MSWM. Overall, it aimed at assessing the efficiency of MSWM systems in terms of technical resource utilisation, reduced environmental impacts and the promotion of circularity.

- Model 2 – economic model (Fig. 2) with CRS

Inputs: Private investment related to CE.

Outputs: Recycle rate, circular material use rate.

This model focused on the economic aspects of MSWM, particularly within the CE context. Overall, it aimed at assessing the economic efficiency of MSWM systems in terms of their CE contributions. Analysing the relationship between inputs (i.e., private investment) and outputs (i.e., waste recycling, material recovery), it provided insight into the economic viability and sustainability of circular waste management practices.

- Model 3 – Sustainability model (Fig. 3) with CRS

Inputs: Private investment related to CE, persons employed in CE, GHG emissions.

Outputs: Recycle rate, circular material use rate.

The sustainability model was designed to evaluate the sustainability performance of MSWM systems across environmental, economic and social dimensions. By integrating inputs from each of these three sustainability criteria (investment, employment and GHG emissions), the model offered an assessment of MSWM performance. Previous studies have employed GHG emissions data to analyse waste management efficiency (Halkos and Petrou, 2019a, 2019b; Ye et al., 2022), considering GHG emissions as 'bad output' to be minimised. In the present study, Model 3 instead treated GHG emissions as an input in the DEA framework, following one of the suggested approaches by Halkos and Petrou (2019d). This allowed for an evaluation of the efficiency and effectiveness of CE practices in achieving sustainability goals, while also providing insights for decision making aimed at fostering holistic and integrated waste management.

For each model, we adopted an output-oriented approach, measuring a country's efficiency in maximising outputs from given levels of inputs. For example, in Model 1, we assumed that countries were primarily focused on increasing their rates of recycling and circular material use, while keeping other inputs constant.

Despite their distinct emphases on technical, economic and sustainability aspects, all models converged on the same two outputs: the recycling rate and material circularity rate for MSW. This alignment underscores the critical importance of these two metrics in assessing MSWM effectiveness and progress towards circularity and sustainability goals.

By consistently evaluating the proportion of waste recycled and the extent of circular material use, these models offered a framework for measuring and benchmarking MSWM. This harmonisation enabled an analysis integrating technical, economic and sustainability perspectives, providing insights into the economic, environmental and social impacts of MSWM strategies, to support decision makers. While each of the three models produced unique findings, their shared focus on recycling and material recovery rates underscores the significance of these metrics for advancing CE principles and sustainable waste management practices.

In our models, we employed both absolute values and ratio (percentage) values as inputs and outputs. However, the use of ratios alongside absolute values in DEA can introduce challenges in estimation, particularly affecting the convexity assumption (Dyson et al., 2001; Olesen et al., 2015, 2017). To address this issue, we assessed the robustness of our results by comparing them with the partial robust frontier derived from the order-m results (Daraio and Simar, 2007), which did not assume convexity. Overall, we observed a high rank correlation between our DEA results and the order-m results, as presented in the supplementary materials (Figs. S15–S20).

4. Results and discussion

Quantitative assessments are crucial for enabling decision makers to measure performance, identify corrective actions and reward good behaviour. Given the fundamental importance of the CE to sustainable development, MSW demands attention. Section 4.1 outlines the results of the DEA. Subsequently, Section 4.2 identifies groups and compares these with those identified in the literature. Section 4.3 assesses points of contact between circular and sustainable performance. Finally, Section 4.4 proposes the main limitations of the work.

4.1. Empirical findings of the DEA modelling

This subsection presents the empirical results of the DEA modelling, with Table 3 summarising the efficiency ratings for each of the five years (2017–2021) across the three models. Fig. 4 illustrates the average efficiency scores for the technical, economic and sustainability models

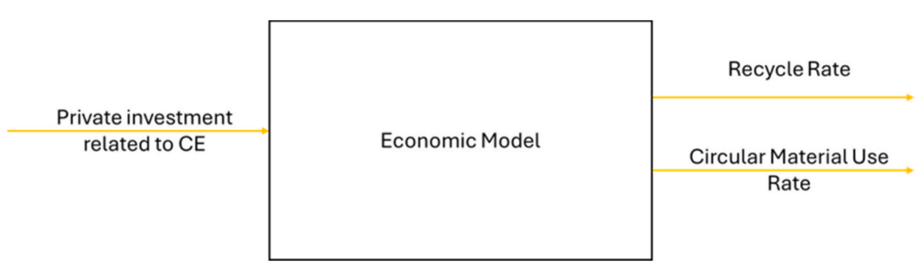

Fig. 2. Economic model. Incoming arrows in the central block indicate model inputs, while outgoing arrows indicate model outputs.

Fig. 3. Sustainability model. Incoming arrows in the central block indicate model inputs, while outgoing arrows indicate model outputs.

Table 3
EU27 efficiency scores for each year considered (2017–2021), by model.

	Technical model					Economic model					Sustainability model				
	2017	2018	2019	2020	2021	2017	2018	2019	2020	2021	2017	2018	2019	2020	2021
AT	0.893	0.897	0.882	1.000	0.959	0.207	0.221	0.221	0.232	0.239	0.914	0.924	0.915	1.000	0.999
BE	0.993	1.000	0.999	0.924	0.984	0.325	0.354	0.308	0.365	0.403	0.848	0.872	0.876	0.953	1.000
BG	0.616	0.597	0.612	0.723	0.504	0.245	0.223	0.246	0.299	0.240	0.483	0.449	0.496	0.532	0.411
CY	0.235	0.239	0.240	0.249	0.201	0.164	0.212	0.293	0.465	0.372	0.211	0.210	0.221	0.376	0.277
CZ	0.536	0.539	0.553	0.643	0.668	0.542	0.619	0.625	0.685	0.679	0.506	0.578	0.597	0.686	0.659
DE	0.969	0.988	0.979	1.000	0.994	0.384	0.348	0.436	0.406	0.400	0.856	0.822	0.897	0.981	0.913
DK	0.677	0.710	0.733	0.640	0.819	0.242	0.280	0.320	0.255	0.318	0.596	0.637	0.678	0.604	0.745
EE	0.679	0.683	0.940	0.936	0.826	0.432	0.414	0.524	0.561	0.541	0.487	0.470	0.615	0.719	0.669
EL	0.310	0.326	0.337	0.299	0.286	0.313	1.000	0.531	1.000	0.930	0.305	0.661	0.345	0.832	0.693
ES	0.654	0.638	0.723	0.844	0.849	0.524	0.530	0.429	0.438	0.428	0.609	0.621	0.697	0.816	0.839
FI	0.660	0.660	0.668	0.618	0.561	0.670	0.700	0.720	0.697	0.644	0.490	0.464	0.575	0.613	0.597
FR	0.863	0.915	0.860	0.977	0.921	0.495	0.580	0.539	0.495	0.557	0.884	0.964	0.911	1.000	0.994
HR	0.564	0.575	0.643	0.715	0.667	0.183	0.167	0.259	0.193	0.233	0.473	0.531	0.622	0.629	0.648
HU	0.891	0.968	0.913	0.770	0.785	0.231	0.244	0.225	0.231	0.268	0.607	0.642	0.631	0.593	0.639
IE	0.614	0.560	0.540	0.580	0.582	1.000	0.933	0.370	0.337	0.338	0.704	0.657	0.527	0.534	0.553
IT	0.899	0.927	0.951	1.000	0.970	0.730	0.639	0.497	0.701	0.646	0.976	0.921	0.911	1.000	0.948
LT	0.839	0.906	0.848	0.762	0.748	0.217	0.373	0.352	0.281	0.275	0.657	0.689	0.637	0.536	0.570
LU	0.710	0.714	0.696	0.751	0.787	0.264	0.380	0.196	0.249	0.274	0.896	1.000	0.936	1.000	1.000
LV	0.564	0.567	0.811	0.777	0.861	0.192	0.165	0.185	0.247	0.313	0.443	0.427	0.687	0.765	0.819
MT	0.404	0.466	0.708	1.000	1.000	0.157	0.198	0.305	0.327	0.277	0.373	0.468	0.719	1.000	0.800
NL	0.946	0.961	0.978	0.976	1.000	0.798	0.614	0.554	0.648	0.679	1.000	0.929	0.919	0.979	1.000
PL	1.000	0.930	0.891	0.966	0.914	0.413	0.278	0.274	0.290	0.316	0.465	0.393	0.386	0.430	0.423
PT	0.492	0.492	0.512	0.534	0.619	0.160	0.144	0.143	0.148	0.188	0.447	0.470	0.498	0.531	0.617
RO	1.000	0.889	0.835	1.000	0.583	0.116	0.138	0.114	0.118	0.112	0.288	0.239	0.244	0.255	0.223
SE	0.972	1.000	1.000	1.000	1.000	0.466	0.570	0.579	0.397	0.496	0.950	0.955	1.000	0.933	0.921
SI	1.000	1.000	0.978	1.000	1.000	0.738	0.753	0.607	0.604	0.619	0.882	0.885	0.889	0.980	1.000
SK	0.700	0.723	0.776	0.825	0.815	0.304	0.301	0.418	0.499	0.499	0.439	0.531	0.616	0.782	0.758

over this period.

Based on the average efficiency scores over the years 2017–2021, the top-performing countries in the technical model were Slovenia, Sweden, Germany, Belgium and the Netherlands. Conversely, the worst performers were Czechia, Ireland, Portugal, Greece and Cyprus. Notably, several countries achieved efficiencies close to the maximum value of 1: Slovenia (0.996), Sweden (0.994), Germany (0.986) and Belgium (0.980) (Fig. S21).

In the economic model, the best performers were Greece, Finland, Slovenia, the Netherlands and Italy. The worst performers were Austria, Latvia, Croatia, Portugal and Romania. Of note, the average efficiency was not high. Greece exhibited the highest efficiency (0.755), followed by Finland (0.686) and Slovenia (0.664) (Fig. S22).

The sustainability model identified Luxembourg, the Netherlands, Sweden, Italy and France as the top performers, and Portugal, Bulgaria, Poland, Cyprus and Romania as the worst performers. The difference between the top two countries was minimal, with Luxembourg and the Netherlands boasting efficiencies of 0.966 and 0.965, respectively. Following closely were Sweden (0.952), Italy and France (both scoring 0.951) (Fig. S23).

The analysis revealed dynamic shifts in efficiency scores across the three models over the study period, as shown in Table S6. Notably, in the technical model, significant improvement was observed in countries such as Czechia, Denmark and Latvia, while Romania demonstrated a decline. Similarly, in the economic model, notable improvement was evident in Greece, Cyprus and Slovakia, while Ireland, Slovenia and the Netherlands showed worsening performance. Furthermore, in the sustainability model, Cyprus, Greece and Malta demonstrated significant improvement, while Ireland and Romania showed decline. These findings underscore the diverse trends in efficiency across European countries, emphasising the need for tailored strategies to address specific areas in need of improvement, as identified by each model.

The maximum efficiency value of 1 was reached by 18 and 12 countries in the technical and sustainability models, respectively. However, the economic model yielded different results, with only 2 countries producing the maximum score (Table S7). The technical model exhibited the highest average efficiency score (0.760) and the highest median (0.787), indicating relatively consistent performance across countries. The range of efficiency scores in this model was also notable, with a standard deviation of 0.214, suggesting significant variability across countries.

In contrast, the economic model recorded the lowest average efficiency score (0.404) and median (0.352), indicating lower overall efficiency compared to the other two models. Additionally, this model displayed the narrowest range of efficiency scores, with a lower standard deviation of 0.207, indicating less variability across countries.

The sustainability model fell between the technical and economic models in terms of the average (0.682) and median (0.657) efficiency scores. However, it exhibited the highest standard deviation (0.229), suggesting greater variability in efficiency compared to the economic

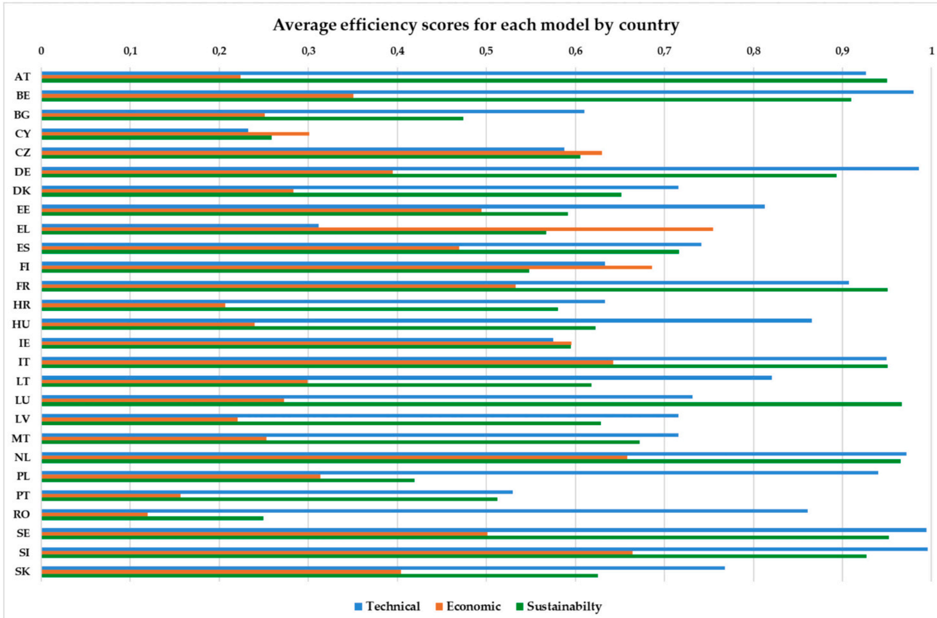

Fig. 4. Average efficiency scores, EU27. Blue bars indicate the results of the technical model, orange bars indicate the results of the economic model and green bars indicate the results of the sustainability model. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

model, but less variability in efficiency compared to the technical model.

4.2. Descriptive group analysis of 27 EU member states

In this section, we identify groups of countries that demonstrated strong performance across the analysed models. Rather than employing 'black box' clustering techniques (which tend to obscure the analytical process), we apply a simple descriptive approach based on medians and quadrant analysis. Although optimization-based clustering approaches have been utilised in previous research (Castillo-Giménez et al., 2019b), we chose this simpler method due to the limited data available. While traditional clustering algorithms (e.g., k-means) are powerful, they can present difficulties when applied to small datasets. Our descriptive approach prioritises interpretability and ease of comprehension, which we posit are crucial in many research contexts. In particular, our method enables a more accessible understanding of the characteristics of different groups, offering clear insights into data structures that might otherwise be obscured by more opaque techniques.

In our discussion of the previous results, we highlighted specific aspects of waste management related to the technical and economic dimensions, alongside more general aspects related to the sustainability dimension. However, despite emphasising different inputs and perspectives, each of the three models shared common outputs: the recycling rate of municipal waste and the rate of material use in the CE.

The economic model assessed economic efficiency within a CE framework, while the technical model evaluated technical resource use. Integrating the inputs and outputs of the economic and technical models, the sustainability model provided a more holistic understanding of sustainable waste management practices, incorporating economic, environmental and social dimensions.

To compare model performance, we created two scatterplots, each based on the average efficiencies of the three models over the study period (2017–2021). The first scatterplot illustrated the relationship between sustainability and technical efficiency (Fig. 5), while the second illustrated the relationship between sustainability and economic efficiency (Fig. 6). This approach aimed at identifying whether countries

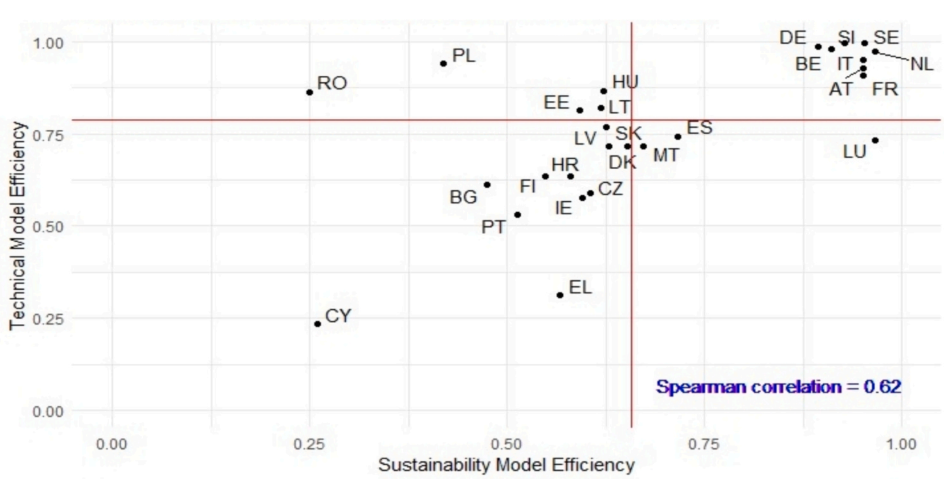

Fig. 5. Sustainability versus technical efficiency.

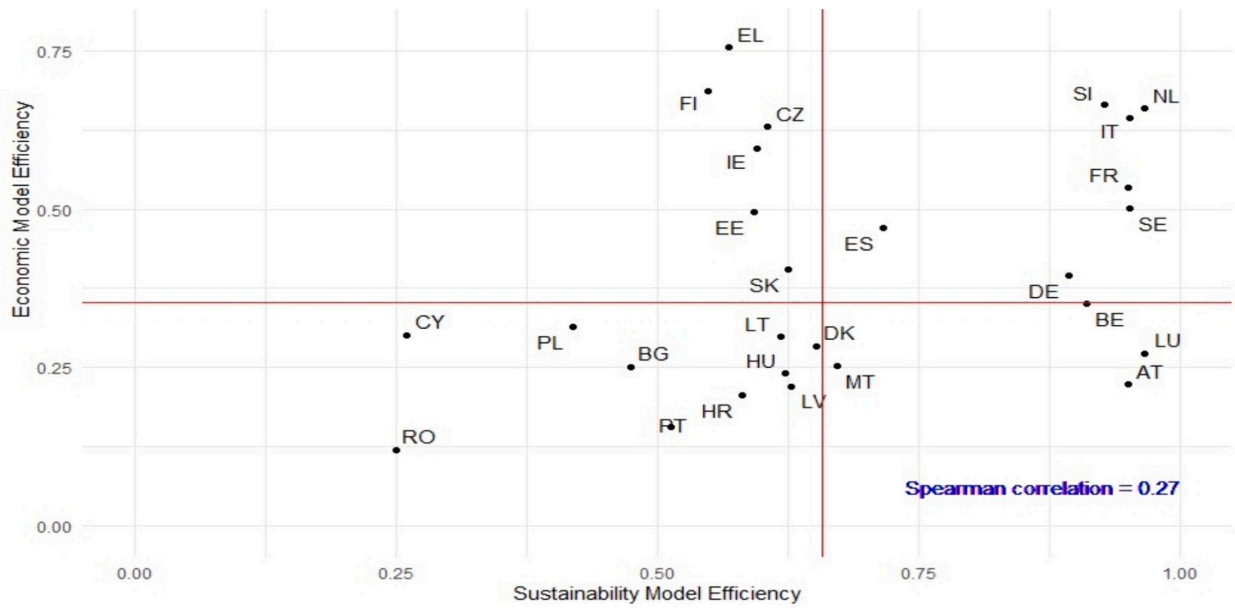

Fig. 6. Sustainability versus economic efficiency.

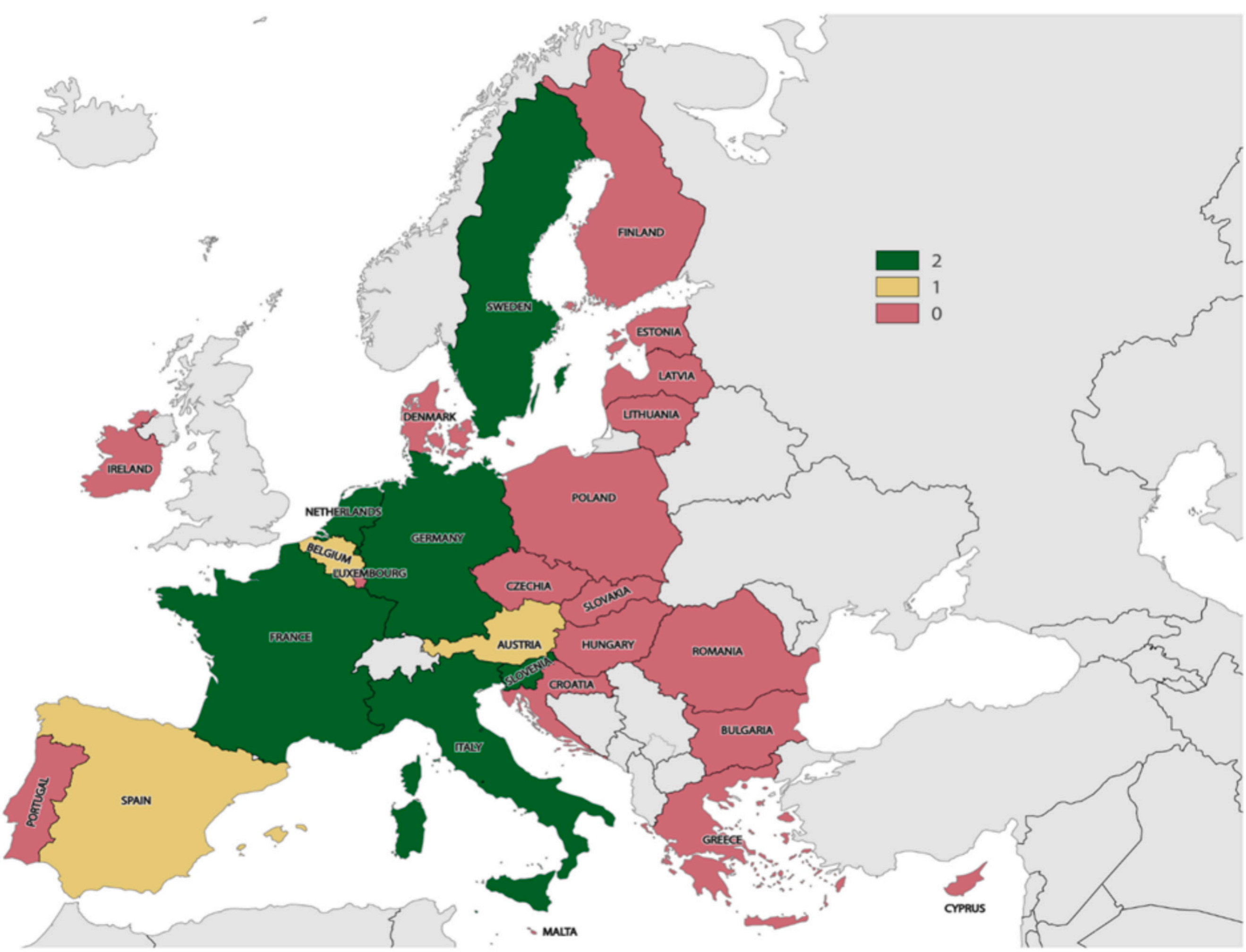

Fig. 7. Efficiency groups map, with country efficiency groups depicted in green (2), yellow (1) and red (0). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

achieved high sustainability efficiency due to both technical and economic proficiency, or whether efficiency in one dimension had a disproportionate impact on overall sustainability efficiency.

In the scatterplots, red lines represent the medians, dividing each plot into four quadrants. As noted in the summary of efficiencies, the median efficiencies for the technical, economic and sustainability models were 0.787, 0.257 and 0.657, respectively. These quadrants formed the basis of a descriptive group analysis, wherein we examined the frequency with which each country appeared in the upper right quadrant (termed the 'UP' quadrant), indicating high scores for both sustainability and either technical or economic efficiency. This analysis provided valuable insight into the concentration of countries excelling with respect to multiple efficiency measures.

Of note, the scatterplot for sustainability versus technical efficiency demonstrated a Spearman correlation coefficient of 0.62, indicating a moderately strong positive correlation between these variables. Conversely, the scatterplot of sustainability versus economic efficiency had a Spearman correlation coefficient of 0.34, indicating a weaker positive correlation between these variables. Reflecting on these results, the strong correlation between technical efficiency and sustainability underlines the importance of technological progress in improving sustainability, in alignment with Vacchi et al. (2021), who emphasised that technological innovation acts as a catalyst for sustainable behaviour. The close relationship between innovation and sustainability suggests the emergence of technological sustainability as a potential fourth dimension of sustainable development. Conversely, the weaker positive correlation between economic efficiency and sustainability implies a divergence in the weight attached to environmental and social variables compared to economic factors. This suggests that economic considerations may not fully capture the environmental and social dimensions of sustainability, as indicated by the modest correlation coefficient of 0.34. In addition, it may be useful to support the development of sustainable communities, emphasising youth education, collaboration among diverse stakeholders and unselfish behaviour.

Groups were identified based on the distribution of countries across the scatterplots (Fig. 7). Countries received a score of 2 if they appeared in the UP quadrant twice, 1 if they appeared in the UP quadrant once, and 0 if they never appeared in the UP quadrant.

This analysis identified six countries with a score of 2 and three with a score of 1. Notably, most countries (i.e., 18) had a score of 0, and the Netherlands, Slovenia, France, Italy, Germany and Sweden each achieved a score of 2. Austria and Belgium scored 1, due to their presence in the UP of only the sustainability versus technical efficiency scatterplot. Spain also scored 1, indicating its presence in the UP of only the sustainability versus economic efficiency scatterplot. Luxembourg and Austria, despite being on the edge of the UP in both scatterplots, scored 0.

We will now proceed to compare the results of the group analysis (Fig. 7) with the bar graphs presented previously (Figs. S21–S23), showing the top five performers in each model. The following findings are noteworthy:

- the Netherlands, which scored 2, was among the top five for all three models;
- Slovenia, Italy and Sweden, also scoring 2, were among the top five for two of the three models;
- among the countries that scored 2, only Germany and France were among the top five for any model (i.e., the technical and sustainability models, respectively);
- despite scoring 1, Austria, Belgium and Spain failed to appear in the top five for any model;
- Greece, Estonia and Luxembourg each appeared in one top five, despite scoring 0 in the groups.

The latter finding indicates that not all countries with a score of 0 performed equally across the different efficiency measures. Thus, the group analysis provided a nuanced picture of the variation in efficiency across countries, highlighting the importance of considering individual country contexts and the factors that might influence national performance.

Turning to the weakest performers, Cyprus, Greece, Bulgaria and Portugal demonstrated the worst efficiency in the technical versus sustainability scatterplot, and Romania, Cyprus, Poland, Bulgaria and Portugal emerged as weakest in the economic versus sustainability scatterplot. Of note, Poland and Romania scored above the median for technical efficiency, while Greece was a top performer for economic efficiency. Nonetheless, all the aforementioned countries scored 0 in the group analysis.

The present findings largely align with those of Castillo-Giménez et al. (2019a), with notable exceptions for Denmark and Luxembourg, which both scored 0. Castillo-Giménez et al. (2019a) applied the full waste hierarchy scale for MSW and relied on data spanning the years 1995–2016, which may account for some of the differences in the results. Furthermore, our findings correspond with the recycling rate performance estimated by Hondroyiannis et al. (2024b), highlighting the efficiency of Germany in the technical model and the comparably lower efficiency of Cyprus. Additionally, while some authors have highlighted the excellence of northern and central EU regions (Chioatto et al., 2024), our results also showed strong performance by Italy and Spain. Chioatto et al. (2024) identified high-performing regions in Ireland, Denmark and Finland, albeit focusing on NUTS-2 regions, making direct comparisons difficult. Previous research by Anselmi et al. (2024), based on MCDA over the years 2018–2020, proposed useful data. In these findings, Luxembourg and Bulgaria outperformed our efficiency-based rankings in waste circularity, while Sweden performed in the opposite direction. Similarly, another analysis (Colasante et al., 2022) confirmed our findings for Germany and Slovenia in the waste circularity index for MSW, especially in the top five rankings. However, this study focused exclusively on recycling, which may explain some of the differences compared to our efficiency-based analysis. Moreover, differences with other works may stem from variations in the research objectives. Studies focussing on the environmental performance of MSW treatment have typically confirmed the consistency of our results for countries in northern and central Europe, including Sweden, Germany and Belgium (Ríos and Picazo-Tadeo, 2021). In our descriptive groups, Finland was placed in group 0, while Halkos and Petrou (2019a) highlighted the overall strong performance of this country across all of their analysed models. These contradictory results may be attributed to the use of different input-output variables. Our results also differ from those of Castillo-Giménez et al. (2019b), who classified Denmark and Luxembourg as top performers in the efficiency analysis, and Ye et al. (2022), who positioned Italy as underperforming in waste treatment.

We feel it is important to address our ranking of Denmark, as most of the literature presents Denmark as a top performer in various aspects of MSWM and circularity. Our DEA models failed to adequately reflect Denmark's exceptional performance in terms of the rate of recycling and investment in the CE sector. Several reasons account for this:

- Denmark demonstrated the highest municipal waste generation per capita in the EU27 and the second-highest GHG emissions per capita from production activities, which negatively affected its technical efficiency score.
- While Denmark ranked first in the EU for disposal with energy recovery (averaged over 2017–2021), our bottom of the waste hierarchy indicator aggregated this score with landfilling (for which Denmark ranked 22nd in the EU27) and incineration (for which Denmark reported 0 kg per capita), which significantly affected its technical efficiency score.

We do not wish to penalise energy recovery, which is preferable to incineration and disposal, in accordance with the waste hierarchy. Similarly, this option should not detract from good recycling and reuse practices.

4.3. Discussion: comparison of sustainability efficiency and the circularity index

CE models may play a critical role in advancing the SDGs, and particularly SDG 12, by fostering sustainable waste management practices (D'Adamo et al., 2024a). In turn, effective management of MSW is instrumental for promoting circular applications (Clasen et al., 2024). To further explore the results of our sustainability model, we compared the sustainability efficiency scores with results for a CE indicator integrating data from multiple Eurostat indicators, with scores ranging from 0 to 1 (D'Adamo et al., 2024b). In the present study, MCDA was used to assess the performance of 27 European countries in 2019 and 2020, assigning equal weight to 15 indicators across five Eurostat categories: (1) production and consumption, (2) waste management, (3) secondary raw materials, (4) competitiveness and innovation and (5) global sustainability and resilience. The CE indicator was subsequently calculated for both 2019 and 2020, and the results were compared with the sustainability efficiency scores over the same period. Fig. 8 presents the comparison under the baseline scenario, in which the indicator weights were determined by academic experts, while Fig. S24 analyses the alternative scenario, in which all indicators were equally weighted.

The first result was a lack of significant difference between the two comparisons. Notably, the main difference related to the case of Slovakia, which, in Fig. 8, marginally deviated from its positioning in the UP quadrant within Fig. S24. Of note, the correlation between efficiency scores and the CE indicator was not particularly high, with a Spearman correlation of 0.49 (0.48 in the alternative scenario). This suggests a lack of significant difference in the relationship between sustainability efficiency and the CE indicator between the two scenarios.

Ten countries were situated in the UP quadrant of the scatterplots (i.e., Belgium, the Netherlands, Slovenia, Italy, Sweden, Germany, France, Austria, Spain, Latvia). A comparison between this scatterplot and the group analysis revealed that six countries in the UP quadrant also achieved a score of 2 in the group analysis, indicating coherence in the results: the Netherlands, Slovenia, Italy, Sweden, Germany and France. Three countries (i.e., Austria, Spain, Belgium) fell within the group defined by a score of 1. Latvia was affiliated with the group scoring 0. However, considering that this scatterplot pertained to the years 2019–2020, it can be inferred that Latvia significantly improved its sustainability efficiency during this period, leading to its placement in the UP quadrant of the scatterplot.

Outliers such as Malta and Luxembourg, which exhibited high sustainability efficiency but comparatively lower scores on the CE indicator, merit our attention, due to a potential discrepancy between sustainability performance and circularity. In general, smaller countries tended to exhibit considerable variation in efficiency. Specifically, Malta demonstrated significant improvement in sustainability efficiency over the study period (from 0.468 in 2018 to 0.719 in 2019 and 1 in 2020). Luxembourg, on the other hand, fell below the median for both technical and economic efficiency, demonstrating minimal disparity. Upon closer examination of the CE indicator, Luxembourg and Malta recorded very low values for one-third of the component variables.

Weak performance was evident for Cyprus and Romania, which were situated in the lower left quadrant. Similarly, poor results emerged for Poland, which demonstrated weak sustainability performance and circularity metrics hovering near the borderline. Portugal and Bulgaria also exhibited poor sustainability performance.

4.4. Limitations

A possible limitation of our models lies in the use of inputs and outputs expressed in both absolute and ratio (percentage) values, which may have created some problems in the estimation of efficiency scores. To address this, we examined the robustness of our findings by comparing them with the partial robust frontier derived from the order-m results, which did not assume convexity. Overall, we observed a high rank correlation between our DEA results and the order-m results, as shown in the supplementary materials (Figs. S15–S20).

Despite the small reference period (2017–2021) and the limited sample size, which represent notable limitations of the work, the inclusion of the most recent data was essential. Given the small sample size, we assumed technological constancy throughout the period and estimated a unique frontier encompassing all years of data available.

A further limitation pertains to the restricted diversity of waste types analysed, suggesting the need for future research to extend the scope of analysis to other waste categories (e.g., e-waste). Additionally, our use

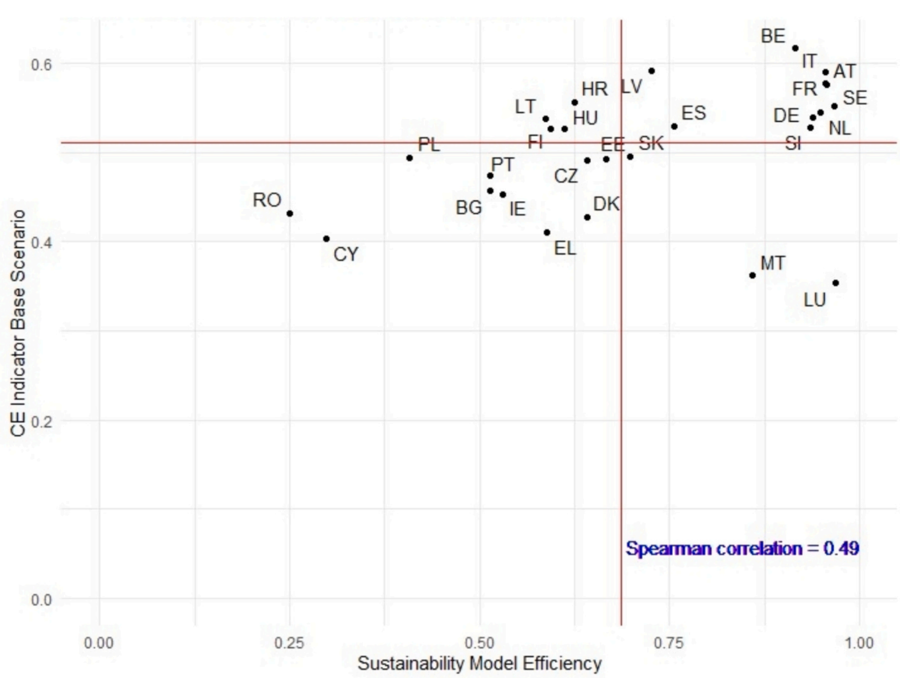

Fig. 8. Sustainability model efficiency versus CE indicator.

of the bottom of the waste hierarchy indicator, combining landfilling and incineration, may have affected the efficiency scores. However, it is important to emphasise once more the importance of energy recovery alongside robust recycling and reuse practices. A further limitation concerns the lack of specific emissions data related to waste management activities. Notwithstanding these limitations, our analysis highlights the need to transition towards practices at the top of the waste hierarchy in order to meet the targets set for 2025, alongside greater reuse and recycling of municipal waste.

Another limitation of the present research regards the output-oriented assumption made for the DEA model. Future research could explore alternative DEA variations, such as input-oriented or directional distance function approaches. Finally, greater attention should be paid to the role played by subsidies and taxes across different countries, as these policies have the potential to optimise performance across all of Europe, rather than solely in individual nations.

5. Conclusions

CE models are integral to achieving SDG 12, by preventing waste, promoting effective waste management and ensuring the efficient use of resources. The present SLR revealed a focus in the literature on quantitative models fostering reuse and recycling within MSW, thereby driving circular practices. The thematic map emphasised the strategic importance and relevance of the interrelated issues of waste management, recycling and municipal solid waste. Thus, the research proposed three distinct models for identifying the optimal frontier for municipal waste recycling rates and circular material use, yielding several key observations.

First, a moderate correlation emerged between technical and sustainability dimensions, whereas a weaker correlation was observed between economic and sustainability dimensions. Sustainability has reshaped both economic patterns and stakeholder relationships. While the present study did not directly assess the effect of globalisation, it is evident that unfair competition among high-carbon economies undercuts sustainability principles through the provision of lower prices, which attract certain consumers. The sustainable production and consumption model calls for businesses to change their production patterns, while also underscoring the involvement of consumers, who require economic opportunities to access affordable and sustainable products. In this direction, technological advancements could facilitate the exploitation of economies of scale and experience, rendering sustainable development competitive with alternatives based on fossil fuels.

The second element that emerged from the present study is that, despite Europe's ambitious plan to become the first climate-neutral continent, it currently appears highly fragmented. Of note, the analysis identified six countries as high-performing leaders: the Netherlands, Slovenia, France, Italy, Germany and Sweden. Positive performance was also recorded for Spain, Austria and Belgium, while Cyprus, Portugal and Bulgaria exhibited weaker scores. This underscores the necessity for collaborative policies among European countries to mitigate excessive and detrimental competition, fostering models geared towards the development of sustainable communities. In this direction, it will be necessary to minimise the cross-border flow of MSW and to enable each country to adopt technologies to maximise reuse and recycling while, at the same time, minimising unsustainable waste management practices (e.g., use of landfills).

The third result showed the consistency between CE outcomes and sustainable performance. Considering CE outcomes, Latvia joined the nine abovementioned high-performing countries, while Cyprus and Romania emerged as weak, alongside Poland, Portugal and Bulgaria, which exhibited suboptimal sustainable performance. Of note, the dynamic nature of the data underscores the importance of ongoing monitoring to support decision makers.

The results show that achieving the European optimum will require greater synergy among countries with varying levels of MSWM performance. The challenges faced are not only technical, but also political and cultural. Moreover, sustainability goals necessitate a balance to be struck between economic profitability and sustainable consumption, to meet citizen needs. In this context, CE models may support SDG 12 by enabling the more effective use of resources.

CRediT authorship contribution statement

Idiano D'Adamo: Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Cinzia Daraio:** Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Simone Di Leo:** Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Massimo Gastaldi:** Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Edouard Nicolas Rossi:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Data curation, Conceptualization.

Declaration of competing interest

The authors declare no conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.spc.2024.08.022.

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